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Numerical Methods
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                  Bisection Method
                   Definition: The bisection method consists of sucessive approximations to narrows down an interval which contains the root of the function by selecting the
                   subinterval that the function changes sign.
                   Theorem: Let A \subseteq R. If f: A \to R is a continuous function and there exist \hat{x} \in A and x' \in A such that:
                     • \hat{\chi} < \chi'
                     • f(\hat{x})f(x') < 0
                   Then, \exists \ \tilde{x} \in [\hat{x}, x'] such that f(\tilde{x}) = 0. If f'(x) < 0 \ \forall x \in A, then the solution is unique.
  In [1]: # Import
                  import numpy as np
                   import math
                   import sympy # Calculus
                   from sympy import *
                   import time
                   import matplotlib.pyplot as plt
  In [2]: # STANDARD BISECTION METHOD (HALF-INTERVAL SEARCH)
                   def stand_bisection_method(f, lower, upper, error=math.exp(-10)):
                           if f(lower)*f(upper) > 0:
                                   print('Bisection Method fails. Please find a and b such that f(a) < 0 < f(b)')
                           elif f(lower)*f(upper) == 0:
                                   print('Either one or both numbers are root of the polynomial. No need to apply the method.')
                           else:
                                   while abs(upper - lower) > error:
                                          x_m = 0.5*(lower + upper)
                                           print(f'Current middle point = {x_m}')
                                           if f(x_m) == 0:
                                                  break
                                           elif f(x_m) < 0:
                                                  lower = x_m
                                           else:
                                                   upper = x_m
                   Let's evaluate the method perfomance for a function defined as:
                                                                                                                   f(x) = x^3 \cdot exp(-x^2) + sin(x^2)
  In [3]: stand_bisection_method(f = lambda x: x**3*math.exp(-x**2) + np.sin(x**2), lower = -2.5, upper = 1)
                   Current middle point = -0.75
                   Current middle point = -1.625
                   Current middle point = -2.0625
                   Current middle point = -1.84375
                   Current middle point = -1.734375
                   Current middle point = -1.6796875
                   Current middle point = -1.70703125
                   Current middle point = -1.693359375
                   Current middle point = -1.6865234375
                   Current middle point = -1.68994140625
                   Current middle point = -1.691650390625
                   Current middle point = -1.6907958984375
                   Current middle point = -1.69122314453125
                   Current middle point = -1.691436767578125
                   Current middle point = -1.6915435791015625
                   Current middle point = -1.6914901733398438
                   Current middle point = -1.6914634704589844
                   Note, however, that the procedure does not guarantee the uniqueness of a solution.
                   We can also use the bisection method to optimize functions whose solutions lie inside the feasible region.
  In [4]: # LOCAL MAXIMUM/MINIMUM BISECTION METHOD (HALF-INTERVAL SEARCH)
                   def max_bisection_method(f, lower, upper, error=math.exp(-10)):
                           x = symbols('x')
                           f = sympy.sympify(f)
                           f_{prime} = sympy.diff(f,x)
                           f_double_prime = sympy.diff(f,x,2)
                           if f_prime.evalf(subs=\{x: lower\}) > 0 \ and f_prime.evalf(subs=\{x: upper\}) < 0 \ and f_double_prime.evalf(subs=\{x: upper\}) <
                   pper) < 0 and f_double_prime.evalf(subs={x: upper}) < 0: # Check if there is a maximum between two points
                                   if abs(upper-lower) < error:</pre>
                                           return  0.5 * (upper + lower), f.evalf(subs={x: 0.5 * (upper + lower) })
                                   else:
                                           middle = 0.5 * (upper + lower)
                                           if f_prime.evalf(subs={x: middle})*f_prime.evalf(subs={x: lower}) < 0: # Maximum is btw lower and middl</pre>
                                                   return max_bisection_method(f, lower, middle)
                                           else: # Maximum is btw middle and upper
                                                   return max_bisection_method(f, middle, upper)
                           \textbf{elif} \ f\_prime.evalf(subs=\{x: \ lower\}) \ < \ 0 \ \ \textbf{and} \ \ f\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ f\_double\_prime.evalf(subs=\{x: \ upper\}) \ > \ 0 \ \ \textbf{and} \ \ \textbf{and} \ \ \textbf{and} \ \ \textbf{and} \ 
                   upper\}) > 0 and f_double_prime.evalf(subs=\{x: upper\}) > 0: # Check if there is a minimum between two points
                                   if abs(upper - lower) < error:</pre>
                                           return 0.5 * (upper + lower), f.evalf(subs={x: 0.5 * (upper + lower) })
                                           middle = 0.5 * (upper + lower)
                                          if f_{prime.evalf(subs=\{x: middle\})*f_{prime.evalf(subs=\{x: lower\})} < 0: # Minimum is btw lower and middle for the first subsequent of the first subsequent for the fi
                                                   return max_bisection_method(f, lower, middle)
                                           else: # Minimum is btw middle and upper
                                                   return max_bisection_method(f, middle, upper)
                           else: # Otherwise
                                   print('Conditions are not satisfied.')
                   Note that the approach is slightly different from the previous example. In this case, there is a function inside another function in order to avoid the while loop.
                   Target function:
                                                                                                                         f(x) = x^3 \cdot exp(-x^2)
                   implemented_function = 'exp(-1*x**2)*x**3'
                   g1 = np.arange(0, 3, 0.1) # Define the Grid
                   y1 = np.exp(-1*g1**2)*g1**3
                   implemented_function = 'exp(-1*x**2)*x**3'
                   x_max = max\_bisection\_method(f = implemented\_function, lower = 0.5, upper = 1.3)[0]
                   y_max = max_bisection_method(f = implemented_function, lower = 0.5, upper = 1.3)[1]
                   plt.plot(g1, y1)
                   plt.title('Figure: Bisection Method (max)')
                   plt.axhline(y=y_max, color='black', linestyle='-')
                   plt.annotate('local max', xy=(x_max, y_max), xytext=(x_max + 0.8, y_max - 0.25),
                                            arrowprops=dict(facecolor='black', shrink=0.07),)
                   plt.style.use('ggplot')
                   plt.rcParams['figure.figsize'] = [7, 7]
                   plt.show()
                                             Figure: Bisection Method (max)
                    0.3
                    0.2
                                                                                         local max
                    0.1
                     0.0
                                                                       1.5
                                                                                      2.0
                                                                                                     2.5
                            0.0
                                           0.5
                                                         1.0
                                                                                                                   3.0
                   However, the previous method is not able to compute the local optimal value when the derivative is not well-defined.
                   Alternatively, someone could redefine the algorithm to compute global maximum. The initial conditions are supposed to be:
                     • x_1 < x_2 < x_3
                     • f(x_2) > f(x_1)
                     • f(x_2) > f(x_3)
                   Those conditions are essential to rule out the possibility of the optimal values occur at the boundaries.
  In [6]: # GLOBAL MAXIMUM BISECTION METHOD (HALF-INTERVAL SEARCH)
                   def global_bisection_method(f, first_x, second_x, third_x, error=math.exp(-10)):
                           # User input in a list
                           x_{order} = []
                           x_order.append(first_x)
                           x_order.append(second_x)
                           x_order.append(third_x)
                           # Sort list in ascending order
                           x_order.sort()
                           x_1 = x_order[0]
                           x_2 = x_{order[1]}
                           x_3 = x_order[2]
                           if f(x_2) > f(x_1) and f(x_2) > f(x_3):
                                   while abs(x_1 - x_3) > error:
                                          x_M1 = 0.5*(x_1 + x_2)
                                          x_M2 = 0.5*(x_2 + x_3)
                                          if f(x_2) > f(x_{M1}) and f(x_2) > f(x_{M2}):
                                                  x_1 = x_M1
                                                  x_3 = x_M2
                                           elif f(x_M2) > f(x_2) and f(x_M2) > f(x_M1):
                                                  x_1 = x_2
                                                   x_2 = x_M2
                                           else:
                                                   x_3 = x_2
                                                  x_2 = x_M1
                                   print(0.5*(x_1 + x_3))
                           else:
                                   print('Bisection method fails')
                   Target function:
                                                                                                                       f(x) = x^3 - 6x^2 - 15x + 8
  In [7]: global\_bisection\_method(f = lambda x: x**3 - 6*x**2 - 15*x + 8, first\_x = -2, second\_x=0.1, third\_x = 6, error=math.e
                   xp(-20))
                   -1.0000000116880983
                  Newton-Raphson Method
                   Definition: This root-finding algorithm produces better approximations to the root of a real-valued function considering the intersection of x-axis and the
                   tangent of the graph.
                   The method can be derived as follows:
                   Applying the first-order taylor approximation around x_0
                                                                                                                   f(x) \approx f(x_0) + f'(x_0)(x - x_0)
                   Setting f(x) = 0 and solving for x
                                                                                                                    0 = f(x_0) + f'(x_0)(x - x_0)
                                                                                                                     f'(x_0)(x-x_0) = -f(x_0)
                                                                                                                         x - x_0 = -\frac{f(x_0)}{f(x_0)}
  In [8]: # Parameters
                  # max_Iter = Maximum number of Iterations
                  # Iter = Current
                   \# x_0 = initial value
                   # f = function
                   # epsilon = error tolerance
                   # X values list
                   value = []
                   def newton_raphson(f, x_0, max_Iter, epsilon = math.exp(-10) ):
                           x = symbols('x')
                           f = sympy.sympify(f)
                           f_{prime} = sympy.diff(f,x)
                           Iter = 0
                           if abs(f.evalf(subs={x: x_0})) < epsilon:</pre>
                                   return x_0
                           else:
                                   while Iter < max_Iter and abs(f.evalf(subs={x: x_0})) > epsilon:
                                           x_new = x_0 - f.evalf(subs=\{x: x_0\})/f_prime.evalf(subs=\{x: x_0\})
                                           value.append(x_new)
                                           x_0 = x_new # Redefine variables inside the loop
                                           Iter = Iter + 1
                                   return value
                   Target function:
                                                                                                                   sin[4 \cdot (x - \frac{1}{4})] + x + x^{20} - 1
  In [9]: print(newton_raphson(f = 'sin(4 * (x - 1/4)) + x + x**20 - 1', x_0 = 0.2 , max_Iter = 25))
                   [0.402970584841736, 0.408262736124847, 0.408293503218815]
                   However, If the initial value x_0 is 0.7, it leads to failure of convergence. Take a look at the last 6 elements.
In [10]: print(newton\_raphson(f = 'sin(4 * (x - 1/4)) + x + x**20 - 1', x_0 = 0.7, max_Iter = 70)[-7:-1])
                   [-1.12524205622660, -1.07551192375073, -1.03573190690332, -1.01118321640315, -1.00300504085853, -1.00225273554209]
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